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AUTOMATIC INDIVIDUAL HOLSTEIN FRIESIAN CATTLE IDENTIFICATION VIA SELECTIVE LOCAL COAT PATTERN MATCHING IN RGB-D IMAGERY

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ABSTRACT

The objective of this paper is the fully automated visual identification of individual Holstein Friesian cattle from dorsal RGB-D imagery taken in real-world farm environments. Autonomous and non-intrusive cattle identification could provide an essential tool for economically-viable mechanised farming analytics, social monitoring, cattle traceability, food production management and more. We contribute a dataset and propose a system that can reliably derive animal identities from top-down stills by first depth-segmenting animals in RGB-D frames, and then extracting a subset of local ASIFT coat descriptors predicted as sufficiently individually distinctive across the species. Predictions are generated by a support vector machine (SVM) using radial basis function (RBF) kernels for predictions based on the ASIFT descriptor structure. We show that learning such a species-specific ID-model is effective, and we demonstrate robustness to poor or complex input image conditions such as more than one cow present, bad depth segmentation, etc. The proposed system yields 97% identification accuracy over testing on approximately 86,000 image pair comparisons covering a herd of 40 individuals from the FriesianCattle2015 Dataset.

Index Terms— Animal Biometrics, Cattle identification, ASIFT, Support Vector Machine, Holstein Friesian Cows

1. INTRODUCTION

Applicational Motivation. Holstein Friesian cattle or ‘dairy cows’ are the highest milk yielding species [1], representing the majority of cattle species in the UK in 2005 [2]. More generally, the bovine industry is economically significant globally, producing over \$3.5 billion in beef and veal exports in the US in 2010 alone [3]. Current export requirements and consumer demand require visual identification of live-stock [4]. Typically achieved via manual labelling (e.g. ear tags, branding, tattooing [4]) or electronically [5], identification contributes towards improved cattle traceability, social

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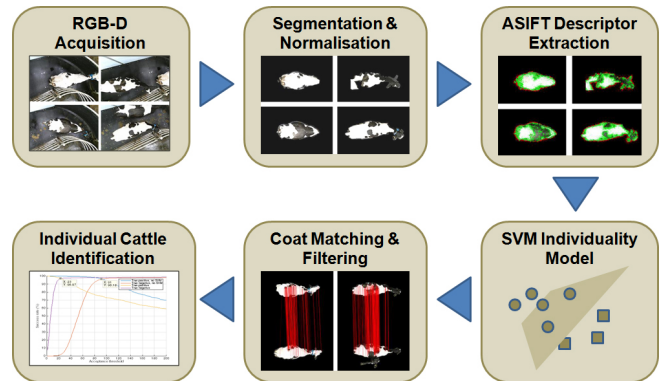


Fig. 1. Proposed Cattle ID Approach. The system segments animal regions via fitting a depth model, and then extracts ASIFT descriptors over the detected area. An SVM is used to learn a species-wide predictor of descriptor-individuality employed to select and use features for cattle identity recovery.

monitoring, food production management, control of disease outbreak and more. Commonly throughout agriculture, cattle, sheep and others are manually identified via the use of ear tags containing an identification number. For European cattle, two ear tags (for redundancy) and a Bovine Identification Document (BID) are mandated by European Parliament regulation 820/97 [6]. However, both [7] and [8] voice concern about the success of manual tagging identification methods. Primarily, the tag is subject to being lost or damaged beyond recognition. Furthermore, animal welfare is called into question as tags may permanently damage or alter an animal’s ear. Identification via ear tags is also performed manually and is, therefore, subject to human-error. Accordingly, the automation of visual identification of individual cattle would provide several new avenues of efficiency and economic advantage with respect to the farming of cattle or livestock generally.

1.1. Related work

Various different approaches to improving cattle identification are published. Attempting to improve current manual ear tag identification, [9] employs automated image-based recognition of ear tag characters and matching against corresponding Bovine Identification Documents. In contrast, existing

non-intrusive, semi-automated methods rely upon facial features overall [10] or muzzle pattern and structure [11, 12, 13, 14]. In [10], a facial representation of cattle is constructed based on local binary pattern (LBP) texture features. Encouraging results are achieved, however, user intervention is required in pre-processing input (training and testing) images to separate cattle faces. As far back as in 1922, [15] introduced cattle muzzle patterns as an individually unique dermatoglyphic trait - similar to a human fingerprint. [16] extends this to find significant differences in muzzle dermatoglyphics across difference breeds. The authors of [11] use muzzle pattern individuality for cattle identification. They employ SIFT [17] for feature extraction and matching upon cattle muzzle prints. Whilst the physical muzzle print must be acquired manually by applying ink to the cattle’s muzzle, the SIFT-based solution does not require pre-processing following scanning of the print. Somewhat similarly, [12] employs SIFT and Random Sample Consensus (RANSAC), now a standard pipeline in computer vision, for feature extraction and matching respectively to achieve 93.3% identification accuracy. The solution is applied to muzzle images directly, removing the manual data acquisition stage required in [11].

1.2. Current Coat Pattern Identification Approaches

Holstein Friesian cattle exhibit individually-distinctive black and white (or brown and white) patterns and markings over their bodies. Dorsal patterns (see Fig. 1 for examples) alone form complex visual alignments which are, as we will show, usable for robust visual identification. First attempts to utilise the cattle’s coat structure for identification exist [18]; essentially using the Scale Invariant Feature Transform (SIFT) algorithm [17] to characterise coat individuality. The technique identifies image features via a staged filtering approach and is invariant to four out of six affine transformation parameters. Using 3D measurements, [19] use Kinect captures to produce RGB-D data to perform identification & depth segmentation.

However, identification difficulties arise in unconstrained imagery from varying viewpoints and the non-rigidity of animals, that is, their skin deformation due to changes in pose and articulation. It is for this reason that in this paper we will employ the recent, fully affine-invariant feature extraction algorithm ASIFT [20] to explicitly model affine deformations of the cattle coat. Thereby increasing the number and quality of the matchable baseline compared to alternative local descriptor techniques such as SIFT [17]. Secondly, we will suggest limiting the descriptor set used for matching to just an ASIFT subset, one that can be learnt to encode individuality of cattle coats reliably. The paper will show that when applied to depth segmented dorsal cattle coat regions, this approach is able to reliably identify individual Holstein Friesian cattle. To the best of our knowledge this paper proposes the first cattle coat identification system that combines depth-segmentation with a species-wide individuality model on local descriptors.

2. RGB-D CATTLE DATASET

2.1. Data Capture in a Farm Environment

Data acquisition was implemented at Wyndhurst Farm at Langford, United Kingdom filming cows exiting the milking file. We employed a top-down operating Kinect 2 sensor and a dedicated workstation for aligned RGB-D recording via the Kinect for Windows SDK 2.0 [21].

Data was captured from an overhead perspective approximately 4m above the ground, where, 16bit depth data at 512x424 and raw RGB video at 1920x1080 and 30fps were recorded. We used a setup running Windows 8.1 on an Intel Core i7-4790K 4.00GHz Socket LGA1150 Processor with a 2048MB GDDR5 PCI-Express Graphics Card and Team-Group Elite Black 16GB (2x8GB) DDR3 RAM. The datasets were generated by encoding a subset of frames into individual PNGs and JPEGs.

2.2. Preprocessing: D-Segmentation and Normalisation

Cattle in the frame are first segmented against background and normalised for rotation. To do this, the depth maps are thresholded at empirically determined maximum and minimum sensor distances ($t_1 = 3.4m, t_2 = 2m$), then binarised such that silhouettes are generated for the cows in the frame. Secondly, erosion and dilation are used to perform hole-filling on these silhouettes.

The resulting intermediates contain clutter in the scene at the same height as the cows and secondary cows that are only partially in the camera’s field of view. Connected component analysis is used to remove any blobs smaller than “cow size” from the camera’s viewing perspective. Finally, principal component analysis is applied to each of the blobs and the major axis (1st principal component) is utilised to rotate each of the masks and its corresponding RGB data such that it is aligned with the horizontal axis.

This process yielded the dataset used here. The Friesian-Cattle2015 Dataset consists of 764 RGB-D image pairs of 92 individuals. Figure 4 provides example images from this dataset.

3. IMPLEMENTATION

Feature extraction upon images is performed by the C++ distribution of ASIFT [20], which, extends standard SIFT by accounting for all affine deformations via simulating camera longitude and latitude coordinates to solve the two affine transformation components missing in SIFT. The remaining 4 parameters are solved for by function calls to SIFT. Extracted ASIFT features are then filtered to limit features to be centred in the animal area by discarding features outside the segmentation boundary as exemplified in Figure 2.

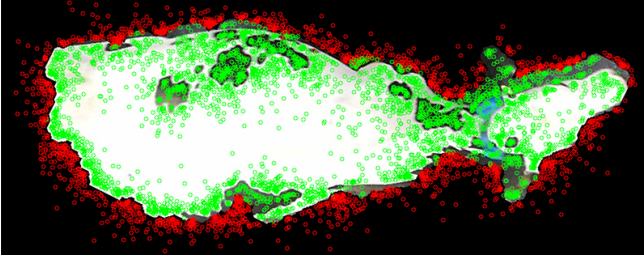


Fig. 2. Extracted ASIFT Features. Features centred outside the depth-segmented region (red) are discarded, the rest (green) are retained.

3.1. Species-specific Model of Descriptor Individuality

Many of the extracted ASIFT features in the animal region still carry little or no information about the identity of the individual – they may encode the highly variable silhouette, the tail or other non-individual features. To learn which subset of descriptor structures is individually characteristic, we trained an RBF-SVM. Particularly, we wanted to predict features as either individually characteristic or not based on the structure of the associated ASIFT descriptors alone. The associated binary ground truth was obtained by thresholding a term $D_f \in [-1, 1]$ for a feature $f \in Cow_x$:

$$D_f = \frac{|M_{intra}|}{|I_{intra}|} - \frac{|M_{inter}|}{|I_{inter}|} \quad (1)$$

where M denotes pairwise feature matches for feature f for matching an image pair of the same individual (intra) or different individuals (inter); I denotes the set of all training pairs employed. High D_f values denote that feature f is distinctive to its class and vice versa. A suitable threshold t was determined following D_f computation upon the training data set. ASIFT features with $D > t$ and $D \leq t$ were labelled positively and negatively, respectively. The feature training set of $\sim 7k$ image pairs (of individuals not used in later testing) together with this supervision data was subsequently provided for SVM training. A grid search was performed a priori in order to determine suitable SVM training values resulting in $C = 2$ and $\gamma = 0.25$. 10-fold cross validation was subsequently completed, achieving 85.6% accuracy on the training data. Threshold value $t = 0.18$ on D was selected; a resulting classification is depicted in Figure 3. The trained SVM is utilised by the subsequent feature matching stage to predict the importance and direct the inclusion of features for consideration during identity recovery.

3.2. Feature Matching and Identification

Image-to-image comparison employing ASIFT feature matching is performed by the released ASIFT C++ implementation [20]. Matching results are sequentially produced by performing feature-to-feature matching upon all possible image

pairs. The results are comprised of the number of common features (matches) found for a particular image pair following filtering, that is, enforcing features to reside within the animal region, and verifying features both geometrically as well as via the individuality model.

Image-image matches are verified geometrically by aligning image pairs vertically (see Figure 4, rows 4, 5: lines between corresponding features forming a match are rendered in red). Only matches/lines which are less than $\pm 3^\circ$ off the median are retained. This equates to a basic, relaxed linear model, which, was found to significantly improve true positive and negative identification success rates. Features are also filtered using the trained SVM. Features comprising a match for an image pair are binarily classified $\in \{-1, 1\}$. Matches where both features are predicted to be characteristic to cattle via the individuality model are retained.

4. EXPERIMENTS

All experiments were conducted with a 2.5 GHz Intel i7 4870HQ processor with 16GB (2x8GB) of DDR3 RAM. Performance analysis for individual identification was accomplished by applying a threshold to the matchings quantity matrix (each test image vs. each test image without self-comparisons). Entries in this matrix contain the number of matched features for every possible image pair following filtering. This threshold is varied to observe the effect upon true positive and true negative identification success rates as illustrated in Figure 5.

To showcase the improvements to scalability via the full individuality model in our approach, we generated two datasets (training and testing) arbitrarily from the larger FriesianCattle2015 Dataset. We use a subset of the collection in order to reduce computational expense. Furthermore, we publish the training/testing dataset used here at the University of Bristol’s data repository. Figure 5 illustrates comparative results via ROC curves. The training dataset sampled from the FriesianCattle2015 Dataset consists of 10

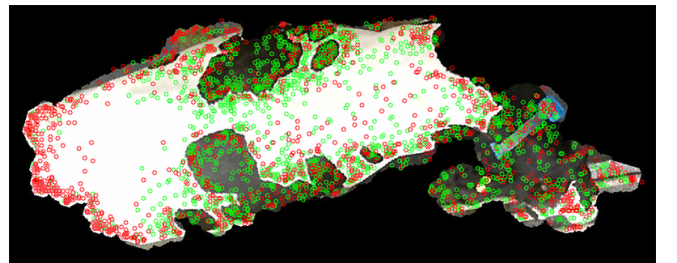


Fig. 3. Application of Individuality Model. Feature acceptance (green) and rejection (red) following thresholding on respective feature D values with $t = 0.18$. Rejected features can be seen to typically sit near highly variable segmentation boundaries.

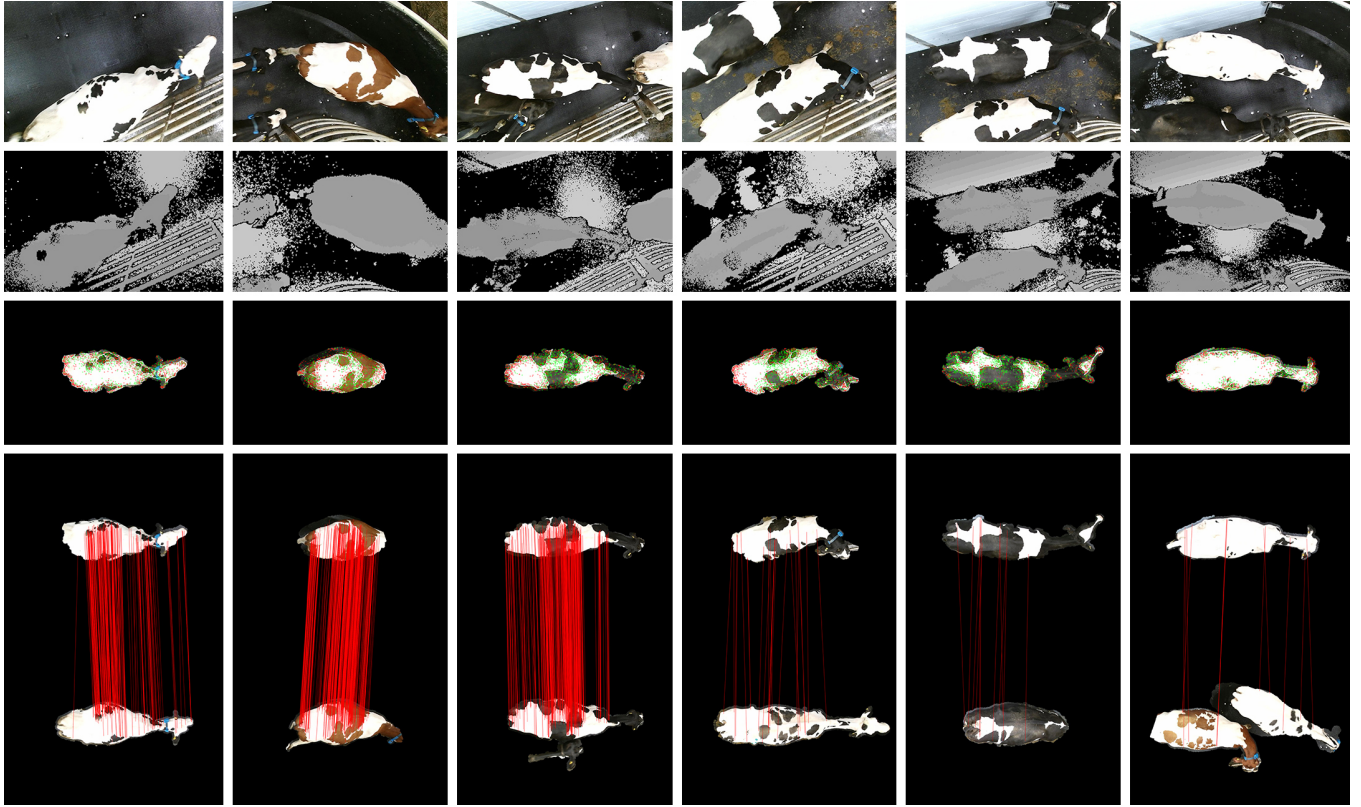


Fig. 4. Examples of Identification Process with Successful and Unsuccessful Image-pair Comparisons. *Row 1:* RGB images and *row 2:* corresponding depths image. *Row 3:* images yielded from pre-processing with retained and discarded features following feature-importance prediction in green and red respectively. *Rows 4, 5:* examples of feature matching and geometric filtering on the same individual (left 3 examples) and different individuals (right 3 examples).

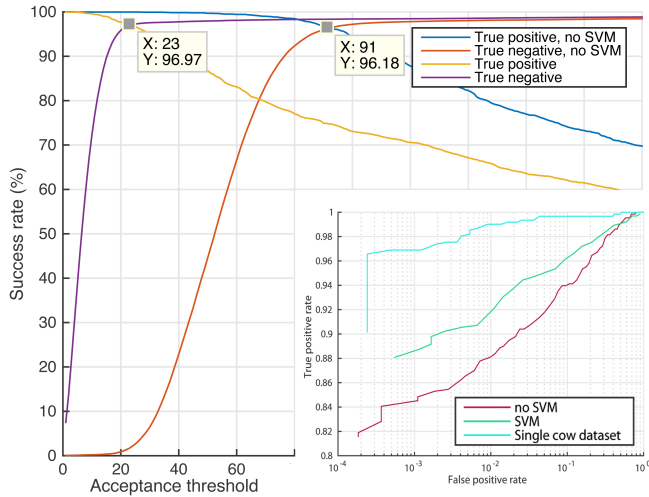


Fig. 5. Results. (Left) True positive and negative success rate vs. the feature acceptance threshold with and without using the individuality model. (Bottom Right) ROC curves confirm effectiveness of individuality model (green) vs. basic ASIFT matching (red), which is appropriate for simple data subset where segmentation results are near perfect (cyan).

individuals, 83 images and the testing dataset consists of 40 individuals, 294 images – yielding approximately 86,000 possible test image pairs. At equal error rate (EER) we achieve 97% identification accuracy on this data (accompanied by 69% feature-importance prediction accuracy). Disabling the individuality model was found to result in a decrease in identification accuracy as given by the ROC curves of Figure 5.

5. CONCLUSION

We find that for an arbitrary subset of the FriesianCattle2015 Dataset, i.e. imagery as can be routinely generated in farm environments, we conclude that the application of an individuality model for filtering local descriptors is beneficial. It led to an average accuracy of 97% during testing over approximately 86,000 image pair comparisons. Generally, we have shown that Holstein Friesian dorsal coat patterns are sufficiently visually distinctive/individual across cattle for identification purposes. We have demonstrated that the proposed approach scales well across small herds. Future work will include applying the techniques proposed here to an unmanned aerial vehicle system for the purpose of social monitoring of herds in outdoor environments.

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